Quasi-Static SIMO Fading Channels at Finite Blocklength

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***Abstract*— We investigate the maximal achievable rate for a given blocklength and error probability over quasi-static single-input multiple-output (SIMO) fading channels. Under mild conditions on the channel gains, it is shown that the channel dispersion is zero regardless of whether the fading realizations are available at the transmitter and/or the receiver. The result follows from computationally and analytically tractable converse and achievability bounds. Through numerical evaluation, we verify that zero dispersion indeed entails fast convergence to outage capacity as the blocklength increases. In the example of a particular 1×2 SIMO Rician channel, the blocklength required to achieve 90% of capacity is about an order of magnitude smaller compared to the blocklength required for an AWGN channel with the same capacity.**

I. Introduction

We study the maximal achievable rate $R^*(n,\epsilon)$ for a given blocklength n and block error probability ϵ over a *quasi-static* single-input multiple-output (SIMO) fading channel, i.e., a random channel that remains constant during the transmission of each codeword, subject to a per-codeword power constraint. We consider two scenarios:

i) perfect channel-state information (CSI) is available at both the transmitter and the receiver;[1]
ii) neither the transmitter nor the receiver have *a priori* CSI.

For quasi-static fading channels, the Shannon capacity, which is given by the limit of $R^*(n,\epsilon)$ for $n\to\infty$ and $\epsilon\to 0$, is zero for many fading distributions of practical interest (e.g., Rayleigh, Rician, and Nakagami fading). In this case, the ϵ-capacity [1] (also known as *outage* capacity), which is obtained by letting $n\to\infty$ in $R^*(n,\epsilon)$ for a fixed $\epsilon>0$, is a more appropriate performance metric. The ϵ-capacity of quasi-static SIMO fading channels does not depend on whether CSI is available at the receiver [2, p. 2632]. In fact, since the channel stays constant during the transmission of a codeword, it can be accurately estimated at the receiver through the transmission of known training sequences with no rate penalty as $n\to\infty$. Furthermore, in the limit $n\to\infty$ the per-codeword power constraint renders CSIT ineffectual [3, Prop. 3], in contrast to the situation where a long-term power constraint is imposed [3], [4].

[1]Hereafter, we write CSIT and CSIR to denote the availability of perfect CSI at the transmitter and at the receiver, respectively. The acronym CSIRT will be used to denote the availability of both CSIR and CSIT.

Building upon classical asymptotic results of Dobrushin and Strassen, it was recently shown by Polyanskiy, Poor, and Verdú [5] that for various channels with positive Shannon capacity C, the maximal achievable rate can be tightly approximated by

$$R^*(n,\epsilon) = C - \sqrt{\frac{V}{n}}Q^{-1}(\epsilon) + \mathcal{O}\left(\frac{\log n}{n}\right). \qquad (1)$$

Here, $Q^{-1}(\cdot)$ denotes the inverse of the Gaussian Q-function $Q(x)\triangleq\int_x^\infty \frac{1}{\sqrt{2\pi}}e^{-t^2/2}dt$ and V is the *channel dispersion* [5, Def. 1]. The approximation (1) implies that to sustain the desired error probability ϵ at a finite blocklength n, one pays a penalty on the rate (compared to the channel capacity) that is proportional to $1/\sqrt{n}$. For the CSIR case, the dispersion of single-input single-output AWGN channels with stationary fading was derived in [6], and generalized to block-memoryless fading channels in [7].

Contributions: We provide achievability and converse bounds on $R^*(n,\epsilon)$ for a quasi-static SIMO fading channel. The asymptotic analysis of these bounds shows that under mild technical conditions on the distribution of the fading gains,

$$R^*(n,\epsilon) = C_\epsilon + \mathcal{O}\left(\frac{\log n}{n}\right). \qquad (2)$$

This result implies that for the quasi-static fading case, the $1/\sqrt{n}$ rate penalty is absent. In other words, the ϵ-dispersion (see [5, Def. 2] or (33) below) of the quasi-static fading channels is zero. This result turns out to hold regardless of whether CSI is available at the transmitter and/or the receiver.

Numerical evidence suggests that, in some scenarios, the absence of the $1/\sqrt{n}$ term in (2) implies fast convergence to C_ϵ as n increases. For example, for a 1×2 SIMO Rician-fading channel with $C_\epsilon = 1$ bit/channel use and $\epsilon = 10^{-3}$, the blocklength required to achieve 90% of C_ϵ is between 120 and 320, which is about an order of magnitude smaller compared to the blocklength required for an AWGN channel with the same capacity. In general, to estimate $R^*(n,\epsilon)$ accurately for moderate n, an asymptotic characterization more precise than (2) is required.

Our converse bound on $R^*(n,\epsilon)$ is based on the meta-converse theorem [5, Thm. 26]. Application of standard achievability bounds for the case of no CSI encounters formidable technical and numerical difficulties. To circumvent

them, we apply the $\kappa\beta$ bound [5, Thm. 25] to a stochastically degraded channel, whose choice is motivated by geometric considerations. The main tool used to establish (2) is a Cramer-Esseen-type central-limit theorem [8, Thm. VI.1].

Notation: Upper case letters such as X denote scalar random variables and their realizations are written in lower case, e.g., x. We use boldface upper case letters to denote random vectors, e.g., $\boldsymbol{X}$, and boldface lower case letter for their realizations, e.g., $\boldsymbol{x}$. Upper case letters of two special fonts are used to denote deterministic matrices (e.g., Y) and random matrices (e.g., $\mathbb{Y}$). The element-wise complex conjugate of the vector $\boldsymbol{x}$ is denoted by $\overline{\boldsymbol{x}}$. The superscripts $^\mathsf{T}$ and $^\mathsf{H}$ stand for transposition and Hermitian transposition, respectively. The standard (Hermitian) inner product of two vectors $\boldsymbol{x} = [x_1 \cdots x_n]^\mathsf{T}$ and $\boldsymbol{y} = [y_1 \cdots y_n]^\mathsf{T}$ is

$$<\boldsymbol{x}, \boldsymbol{y}> \triangleq \sum_{i=1}^{n} x_i \overline{y_i}. \tag{3}$$

The Euclidean norm is denoted by $\|\boldsymbol{x}\|^2 \triangleq <\boldsymbol{x}, \boldsymbol{x}>$. Furthermore, $\mathcal{CN}(\mathbf{0}, \mathsf{A})$ stands for the distribution of a circularly-symmetric complex Gaussian random vector with covariance matrix A. Given two distributions P and Q on a common measurable space $\mathcal{W}$, we define a randomized test between P and Q as a random transformation $P_{Z\,|\,W} : \mathcal{W} \mapsto \{0, 1\}$ where 0 indicates that the test chooses Q. We shall need the following performance metric for the test between P and Q:

$$\beta_\alpha(P, Q) \triangleq \min \int P_{Z\,|\,W}(1\,|\,w) Q(dw) \tag{4}$$

where the minimum is over all probability distributions $P_{Z\,|\,W}$ satisfying

$$\int P_{Z\,|\,W}(1\,|\,w) P(dw) \geq \alpha. \tag{5}$$

We refer to a test achieving (4) as an optimal test. The indicator function is denoted by $\mathbb{1}\{\cdot\}$. Finally, $\log(\cdot)$ indicates the natural logarithm, and $\mathrm{Beta}(\cdot, \cdot)$ denotes the Beta distribution [9, Ch. 25].

II. Channel Model and Fundamental Limits

We consider a quasi-static SIMO channel with r receive antennas. The channel input-output relation is given by

$$\mathbb{Y} = \boldsymbol{x}\boldsymbol{H}^\mathsf{T} + \mathbb{W} \tag{6}$$

$$= \begin{pmatrix} x_1 H_1 + W_{11} & \cdots & x_1 H_r + W_{1r} \\ \vdots & & \vdots \\ x_n H_1 + W_{n1} & \cdots & x_n H_r + W_{nr} \end{pmatrix}. \tag{7}$$

The vector $\boldsymbol{H} = [H_1 \cdots H_r]^\mathsf{T}$ contains the complex fading coefficients, which are random but remain constant for all n channel uses; $\{W_{lm}\}$ are independent and identically distributed (i.i.d.) $\mathcal{CN}(0, 1)$ random variables; $\boldsymbol{x} = [x_1 \cdots x_n]^\mathsf{T}$ contains the transmitted symbols.

We consider both the case when the transmitter and the receiver do not know the realizations of $\boldsymbol{H}$ (no CSI) and the case where the realizations of $\boldsymbol{H}$ are available to both the transmitter and the receiver (CSIRT). Next, we introduce the notion of a channel code for these two settings.

Definition 1: An $(n, M, \epsilon)_{\text{no-CSI}}$ code consists of:

i) an encoder f: $\{1, \ldots, M\} \mapsto \mathbb{C}^n$ that maps the message $J \in \{1, \ldots, M\}$ to a codeword $\boldsymbol{x} \in \{\boldsymbol{c}_1, \ldots, \boldsymbol{c}_M\}$. The codewords satisfy the power constraint

$$\|\boldsymbol{c}_i\|^2 \leq n\rho, \quad i = 1, \ldots, M. \tag{8}$$

We assume that J is equiprobable on $\{1, \ldots, M\}$.

ii) A decoder g: $\mathbb{C}^{n\times r} \mapsto \{1, \ldots, M\}$ satisfying

$$\mathbb{P}[g(\mathbb{Y}) \neq J] \leq \epsilon \tag{9}$$

where $\mathbb{Y}$ is the channel output induced by the transmitted codeword according to (6).

The maximal achievable rate for the no-CSI case is defined as

$$R^*_{\text{no}}(n, \epsilon) \triangleq \sup\left\{ \frac{\log M}{n} : \exists (n, M, \epsilon)_{\text{no-CSI}} \text{ code} \right\}. \tag{10}$$

Definition 2: An $(n, M, \epsilon)_{\text{CSIRT}}$ code consists of:

i) an encoder f: $\{1, \ldots, M\} \times \mathbb{C}^r \mapsto \mathbb{C}^n$ that maps the message $J \in \{1, \ldots, M\}$ and the channel $\boldsymbol{H}$ to a codeword $\boldsymbol{x} \in \{\boldsymbol{c}_1(\boldsymbol{H}), \ldots, \boldsymbol{c}_M(\boldsymbol{H})\}$; the codewords satisfy

$$\|\boldsymbol{c}_i(\boldsymbol{h})\|^2 \leq n\rho, \quad \forall i = 1, \ldots M, \quad \forall \boldsymbol{h} \in \mathbb{C}^r. \tag{11}$$

We assume that J is equiprobable on $\{1, \ldots, M\}$.

ii) A decoder g: $\mathbb{C}^{n\times r} \times \mathbb{C}^r \mapsto \{1, \ldots, M\}$ satisfying

$$\mathbb{P}[g(\mathbb{Y}, \boldsymbol{H}) \neq J] \leq \epsilon. \tag{12}$$

The maximal achievable rate for the CSIRT case is defined as

$$R^*_{\text{rt}}(n, \epsilon) \triangleq \sup\left\{ \frac{\log M}{n} : \exists (n, M, \epsilon)_{\text{CSIRT}} \text{ code} \right\}. \tag{13}$$

It follows that

$$R^*_{\text{no}}(n, \epsilon) \leq R^*_{\text{rt}}(n, \epsilon). \tag{14}$$

Let $G \triangleq \|\boldsymbol{H}\|^2$, and define

$$F_C(\xi) \triangleq \mathbb{P}\left[\log(1 + \rho G) \leq \xi\right]. \tag{15}$$

For every $\epsilon > 0$, the ϵ-capacity C_ϵ of the channel (6) is [1, Thm. 6]

$$C_\epsilon = \lim_{n\to\infty} R^*_{\text{no}}(n, \epsilon) = \lim_{n\to\infty} R^*_{\text{rt}}(n, \epsilon) = \sup\left\{\xi : F_C(\xi) \leq \epsilon\right\}. \tag{16}$$

III. Main Results

We present next a converse (upper) bound on $R^*_{\text{rt}}(n, \epsilon)$ and an achievability (lower) bound on $R^*_{\text{no}}(n, \epsilon)$. The two bounds match asymptotically up to a $\mathcal{O}(\log(n)/n)$ term, allowing us to establish (2).

A. Converse Bound

Theorem 1: Let

$$L_n \triangleq n\log(1+\rho G) + \sum_{i=1}^{n}\left(1 - \left|\sqrt{\rho G}Z_i - \sqrt{1+\rho G}\right|^2\right) \quad (17)$$

and

$$S_n \triangleq n\log(1+\rho G) + \sum_{i=1}^{n}\left(1 - \frac{\left|\sqrt{\rho G}Z_i - 1\right|^2}{1+\rho G}\right) \quad (18)$$

with $G = \|\boldsymbol{H}\|^2$ and $\{Z_i\}_{i=1}^n$ i.i.d. $\mathcal{CN}(0,1)$-distributed. For every n and every $0 < \epsilon < 1$, the maximal achievable rate on the quasi-static SIMO fading channel (6) with CSIRT is upper-bounded by

$$R^*_{\mathrm{rt}}(n-1,\epsilon) \le \frac{1}{n-1}\log\frac{1}{\mathbb{P}[L_n \ge n\gamma_n]} \quad (19)$$

where γ_n is the solution of

$$\mathbb{P}[S_n \le n\gamma_n] = \epsilon. \quad (20)$$

Proof: See Appendix A. ■

B. Achievability Bound

Let $Z(\mathsf{Y}) : \mathbb{C}^{n\times r} \mapsto \{0,1\}$ be a test between an arbitrary distribution $Q_{\mathbb{Y}}$ and $P_{\mathbb{Y}|\boldsymbol{X}=\boldsymbol{x}}$, where $Z = 0$ indicates that the test chooses $Q_{\mathbb{Y}}$. Let $\mathcal{F} \subset \mathbb{C}^n$ be a set of permissible channel inputs as specified by (8). We define the following measure of performance $\tilde{\kappa}_\tau(\mathcal{F}, Q_{\mathbb{Y}})$ for the composite hypothesis test between $Q_{\mathbb{Y}}$ and the collection $\{P_{\mathbb{Y}|\boldsymbol{X}=\boldsymbol{x}}\}_{\boldsymbol{x}\in\mathcal{F}}$:

$$\tilde{\kappa}_\tau(\mathcal{F}, Q_{\mathbb{Y}}) \triangleq \inf Q_{\mathbb{Y}}\left[Z(\mathbb{Y}) = 1\right] \quad (21)$$

where the infimum is over all *deterministic* tests $Z(\cdot)$ satisfying:

i) $P_{\mathbb{Y}|\boldsymbol{X}=\boldsymbol{x}}\left[Z(\mathbb{Y}) = 1\right] \ge \tau$, $\forall \boldsymbol{x} \in \mathcal{F}$,
ii) $Z(\mathsf{Y}) = Z(\widetilde{\mathsf{Y}})$ whenever the columns of Y and $\widetilde{\mathsf{Y}}$ span the same subspace in $\mathbb{C}^n$.

Note that, $\tilde{\kappa}_\tau(\mathcal{F}, Q_{\mathbb{Y}})$ in (21) coincides with $\kappa_\tau(\mathcal{F}, Q_{\mathbb{Y}})$ defined in [5, eq. (107)] if the additional constraint ii) is dropped and if the infimum in (21) is taken over randomized tests. Hence,

$$\kappa_\tau(\mathcal{F}, Q_{\mathbb{Y}}) \le \tilde{\kappa}_\tau(\mathcal{F}, Q_{\mathbb{Y}}). \quad (22)$$

We will need the following definition.

Definition 3 ([10, Def. 4]): Let $\boldsymbol{a}$ be a nonzero vector and let $\mathcal{B}$ be an l-dimensional ($l < n$) subspace in $\mathbb{C}^n$. We define the angle $\theta(\boldsymbol{a}, \mathcal{B}) \in [0, \pi/2]$ between $\boldsymbol{a}$ and $\mathcal{B}$ by

$$\cos\theta(\boldsymbol{a}, \mathcal{B}) = \max_{\boldsymbol{b}\in\mathcal{B},\, \|\boldsymbol{b}\|=1} \frac{|<\boldsymbol{a}, \boldsymbol{b}>|}{\|\boldsymbol{a}\|}. \quad (23)$$

With a slight abuse of notation, for a matrix $\mathsf{B} \in \mathbb{C}^{n\times l}$ we use $\theta(\boldsymbol{a}, \mathsf{B})$ to indicate the angle between $\boldsymbol{a}$ and the subspace $\mathcal{B}$ spanned by the columns of B. In particular, if the columns of B are an orthonormal basis for $\mathcal{B}$, then

$$\cos\theta(\boldsymbol{a}, \mathsf{B}) = \frac{\|\boldsymbol{a}^{\mathsf{H}}\mathsf{B}\|}{\|\boldsymbol{a}\|}. \quad (24)$$

Theorem 2 below establishes a lower bound on $R^*_{\mathrm{no}}(n, \epsilon)$.

Theorem 2: Let $\mathcal{F} \subset \mathbb{C}^n$ be a measurable set of channel inputs satisfying (8). For every $0 < \epsilon < 1$, every $0 < \tau < \epsilon$, and every probability distribution $Q_{\mathbb{Y}}$, there exists an $(n, M, \epsilon)_{\text{no-CSI}}$ code satisfying

$$M \ge \frac{\tilde{\kappa}_\tau(\mathcal{F}, Q_{\mathbb{Y}})}{\sup_{\boldsymbol{x}\in\mathcal{F}} Q_{\mathbb{Y}}[Z_{\boldsymbol{x}}(\mathbb{Y}) = 1]} \quad (25)$$

where

$$Z_{\boldsymbol{x}}(\mathsf{Y}) = \mathbb{1}\{\cos^2\theta(\boldsymbol{x}, \mathsf{Y}) \ge 1 - \gamma_n(\boldsymbol{x})\} \quad (26)$$

with $\gamma_n(\boldsymbol{x}) \in [0,1]$ chosen so that

$$P_{\mathbb{Y}|\boldsymbol{X}=\boldsymbol{x}}[Z_{\boldsymbol{x}}(\mathbb{Y}) = 1] \ge 1 - \epsilon + \tau. \quad (27)$$

Proof: The lower bound (25) follows by applying the $\kappa\beta$ bound [5, Thm. 25] to a stochastically degraded version of (6), whose output is the subspace spanned by the columns of $\mathbb{Y}$. ■

The geometric intuition behind the choice of the test (26) is that $\boldsymbol{x}$ in (6) belongs to the subspace spanned by the columns of $\mathbb{Y}$ if the additive noise $\mathbb{W}$ is neglected.

In Corollary 3 below, we present a further lower bound on M that is obtained from Theorem 2 by choosing[2]

$$Q_{\mathbb{Y}} = \prod_{i=1}^{n} \mathcal{CN}(\mathbf{0}, \mathsf{I}_r) \quad (28)$$

and by requiring that the codewords belong to the set

$$\mathcal{F}_n \triangleq \left\{\boldsymbol{x} \in \mathbb{C}^n : \|\boldsymbol{x}\|^2 = n\rho\right\}. \quad (29)$$

The resulting bound allows for numerical evaluation.

Corollary 3: For every $0<\epsilon<1$ and every $0<\tau<\epsilon$ there exists an $(n, M, \epsilon)_{\text{no-CSI}}$ code with codewords in the set $\mathcal{F}_n$ satisfying

$$M \ge \frac{\tau}{F(\gamma_n; n-r, r)} \quad (30)$$

where $F(\cdot; n-r, r)$ is the cumulative distribution function (cdf) of a $\mathrm{Beta}(n-r, r)$-distributed random variable and $\gamma_n \in [0,1]$ is chosen so that

$$P_{\mathbb{Y}|\boldsymbol{X}=\boldsymbol{x}_0}[Z_{\boldsymbol{x}_0}(\mathbb{Y}) = 1] \ge 1 - \epsilon + \tau \quad (31)$$

with

$$\boldsymbol{x}_0 \triangleq \left[\sqrt{\rho}\,\sqrt{\rho}\,\cdots\,\sqrt{\rho}\right]^{\mathsf{T}}. \quad (32)$$

Proof: See Appendix B. ■

[2]Corollary 3 holds actually for every isotropic distribution on $\mathbb{Y}$.

C. Asymptotic Analysis

Following [5, Def. 2], we define the ϵ-dispersion of the channel (6) via $R^*_{\rm no}(n,\epsilon)$ (resp. $R^*_{\rm rt}(n,\epsilon)$) as follows

$$V_\epsilon^{\rm no} = \limsup_{n\to\infty} n\left(\frac{C_\epsilon - R^*_{\rm no}(n,\epsilon)}{Q^{-1}(\epsilon)}\right)^2, \ \epsilon\in(0,1)\backslash\left\{\frac{1}{2}\right\} \quad (33)$$

$$V_\epsilon^{\rm rt} = \limsup_{n\to\infty} n\left(\frac{C_\epsilon - R^*_{\rm rt}(n,\epsilon)}{Q^{-1}(\epsilon)}\right)^2, \ \epsilon\in(0,1)\backslash\left\{\frac{1}{2}\right\}. \quad (34)$$

The rationale behind the definition of the channel dispersion is that—for ergodic channels—the probability of error ϵ and the optimal rate $R^*(n,\epsilon)$ roughly satisfy

$$\epsilon \approx \mathbb{P}\left[C + \sqrt{\frac{V}{n}}Z \le R^*(n,\epsilon)\right] \quad (35)$$

where C and V are the channel capacity and dispersion, respectively, and Z is a zero-mean unit-variance real Gaussian random variable. The quasi-static fading channel is conditionally ergodic given $\mathbf{H}$, which suggests that

$$\epsilon \approx \mathbb{P}\left[C(\mathbf{H}) + \sqrt{\frac{V(\mathbf{H})}{n}}Z \le R^*(n,\epsilon)\right] \quad (36)$$

where $C(\mathbf{H})$ and $V(\mathbf{H})$ are the capacity and the dispersion of the conditional channels. Assuming that Z is independent of $\mathbf{H}$, we expect that (36) be well-approximated by

$$\epsilon \approx \mathbb{P}[C(\mathbf{H}) \le R^*(n,\epsilon)]\,. \quad (37)$$

Indeed, given $\mathbf{H} = \boldsymbol{h}$, the probability $\mathbb{P}[Z \le (R^*(n,\epsilon) - C(\mathbf{h}))/\sqrt{V(\boldsymbol{h})/n}]$ is close to one in the "outage" case $C(\mathbf{h}) < R^*(n,\epsilon)$, and close to zero otherwise. This observation is formalized in the following lemma.

Lemma 4: Let X be a random variable with zero mean, unit variance, and finite third moment. Let Y be independent of X with twice continuously differentiable probability density function (pdf) f_Y. Then

$$\lim_{n\to\infty} n^{3/2}\left|\mathbb{P}[X\le\sqrt{n}Y] - \mathbb{P}[Y\ge 0] + \frac{f_Y'(0)}{2n}\right| \le k_1 \quad (38)$$

where $k_1 \triangleq (k_2(\delta)/6 + 2\delta^{-3})\mathbb{E}\left[|X|^3\right]$, $k_2(\delta) \triangleq \sup_{t\in(-\delta,\delta)}\max\{|f_Y(t)|, |f_Y'(t)|, |f_Y''(t)|\}$ and $\delta>0$ is chosen so that k_2 is finite.

Proof: See Appendix C. ■

From (36) and (37), and recalling (16) we may expect that for a quasi-static fading channel the maximal achievable rate satisfies

$$R^*(n,\epsilon) = C_\epsilon + 0\cdot\frac{1}{\sqrt{n}} + \text{smaller-order terms}\,. \quad (39)$$

This intuitive reasoning turns out to be correct as the following result demonstrates.

Theorem 5: Assume that the channel gain $G = \|\boldsymbol{H}\|^2$ has a twice continuously differentiable pdf and that C_ϵ is a point of growth of the capacity-outage function (15), i.e.,

$$\left.\frac{dF_C(\xi)}{d\xi}\right|_{\xi=C_\epsilon} > 0. \quad (40)$$

Then, the maximal achievable rates satisfy

$$R^*_{\rm no}(n,\epsilon) = C_\epsilon + \mathcal{O}\left(\frac{\log n}{n}\right) \quad (41)$$

$$R^*_{\rm rt}(n,\epsilon) = C_\epsilon + \mathcal{O}\left(\frac{\log n}{n}\right). \quad (42)$$

Hence, the ϵ-dispersion is zero for both the no-CSI and the CSIRT case:

$$V_\epsilon^{\rm no} = V_\epsilon^{\rm rt} = 0\,, \qquad \epsilon\in(0,1)\backslash\{1/2\}\,. \quad (43)$$

Proof: See Appendix D. ■

The assumptions on the channel gain are satisfied by all probability distributions commonly used to model fading, e.g., Rayleigh, Rician, and Nakagami. However, the standard AWGN channel, which can be seen as a quasi-static fading channel with $G=1$, does not meet these assumptions and in fact has positive dispersion [5, Thm. 54].

D. Numerical Results

Fig. 1 shows the achievability bound (30) and the converse bound (19) for a quasi-static SIMO fading channel with two receive antennas. The channel between the transmit antenna and each of the two receive antennas is Rician-distributed with K-factor equal to 20 dB. The two channels are assumed to be independent. We set $\epsilon = 10^{-3}$ and choose $\rho = -1.55$ dB so that $C_\epsilon = 1$ bit/channel use. For reference, we also plotted a lower bound on $R^*_{\rm rt}(n,\epsilon)$ obtained by using the $\kappa\beta$ bound [5, Thm. 25] and assuming CSIR.[3] Fig. 1 shows also the approximation (1) for $R^*(n,\epsilon)$ corresponding to an AWGN channel with $C=1$ bit/channel use. Note that we replaced the term $\mathcal{O}(\log(n)/n)$ in (1) with $\log(n)/(2n)$ (see [5, eq. (296)]).[4] The blocklength required to achieve 90% of the ϵ-capacity of the quasi-static fading channel is in the range $[120, 320]$ for the CSIRT case and in the range $[120, 480]$ for the no-CSI case. For the AWGN channel, this number is approximately 1420. Hence, for the parameters chosen in Fig. 1, the prediction (based on zero dispersion) of fast convergence to capacity is validated.

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[3]Specifically, we took $\mathcal{F} = \mathcal{F}_n$ with $\mathcal{F}_n$ defined in (29), and $Q_{\mathbb{Y}\boldsymbol{H}} = P_{\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}$ with $Q_{\mathbb{Y}\,|\,\boldsymbol{H}}$ defined in (45).

[4]The validity of the approximation [5, eq. (296)] is numerically verified in [5] for a real AWGN channel. Since a complex AWGN channel can be treated as two real AWGN channels with the same SNR, the approximation [5, eq. (296)] with $C = \log(1+\rho)$ and $V = \frac{\rho^2+2\rho}{(1+\rho)^2}$ is accurate for the complex case [11, Thm. 78].

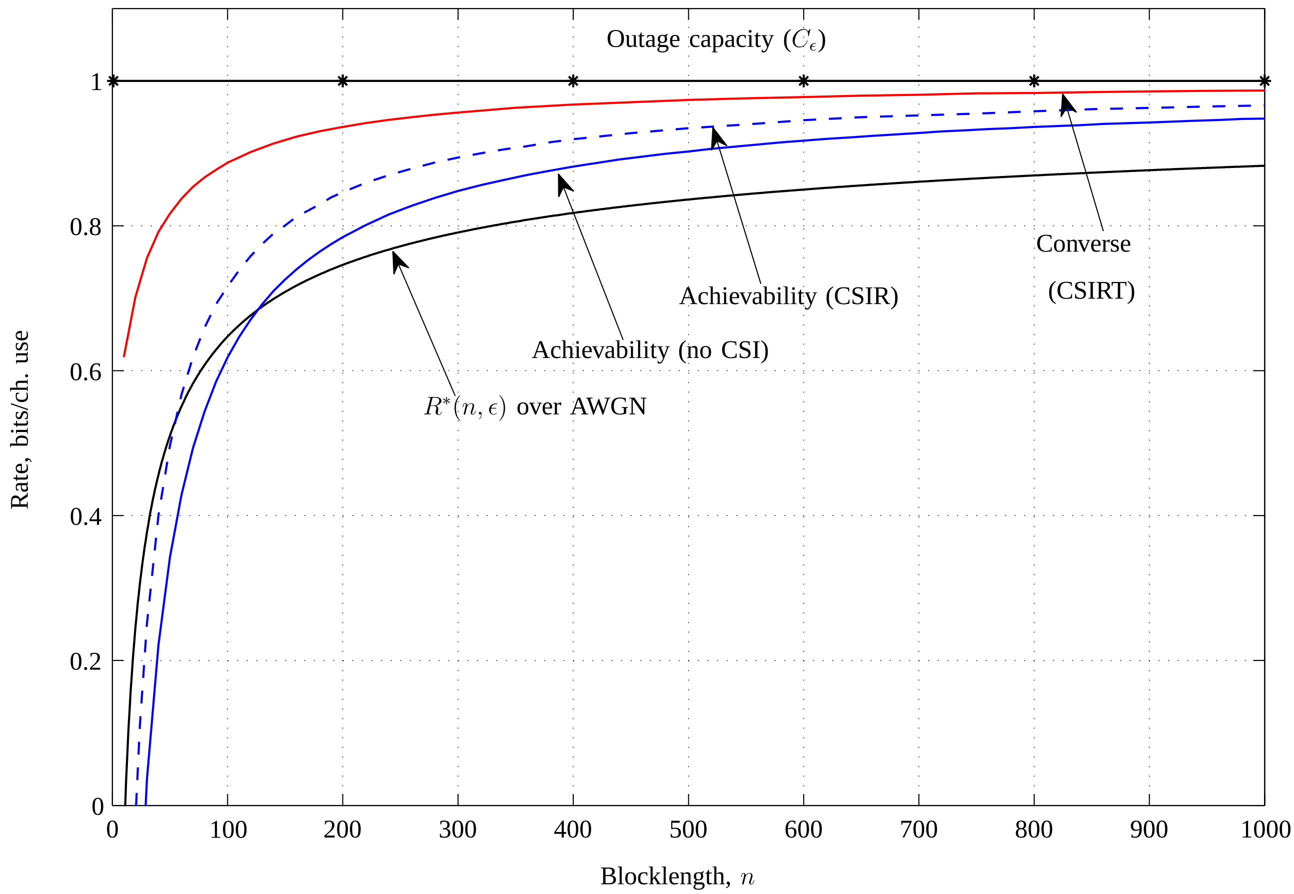

Fig. 1. Bounds for the quasi-static SIMO Rician-fading channel with K-factor equal to 20 dB, two receive antennas, SNR $= -1.55$ dB, and $\epsilon = 10^{-3}$.

Appendix A
Proof of Theorem 1

For the channel (6) with CSIRT, the input is the pair $(\boldsymbol{X}, \boldsymbol{H})$, and the output is the pair $(\mathbb{Y}, \boldsymbol{H})$. Note that the encoder induces a distribution $P_{\boldsymbol{X} \mid \boldsymbol{H}}$ on $\boldsymbol{X}$ and is necessarily randomized, since $\boldsymbol{H}$ is independent of the message J. Denote by $R^*_{\mathrm{e}}(n,\epsilon)$ the maximal achievable rate under the constraint that each codeword $\boldsymbol{c}_j(\boldsymbol{h})$ satisfies the power constraint (11) with equality, namely, $\boldsymbol{c}_j(\boldsymbol{h})$ belongs to the set $\mathcal{F}_n$ defined in (29) for $j = 1, \dots, M$ and for all $\boldsymbol{h} \in \mathbb{C}^r$. Then by [5, Lem. 39],

$$R^*_{\mathrm{rt}}(n-1,\epsilon) \le \frac{n}{n-1} R^*_{\mathrm{e}}(n,\epsilon). \tag{44}$$

We next establish an upper bound on $R^*_{\mathrm{e}}(n,\epsilon)$. Henceforth, $\boldsymbol{x}$ is assumed to belong to $\mathcal{F}_n$. To upper-bound $R^*_{\mathrm{e}}(n,\epsilon)$, we use the meta-converse theorem [5, Thm. 26]. As *auxiliary* channel $Q_{\mathbb{Y}\boldsymbol{H} \mid \boldsymbol{X}\boldsymbol{H}}$, we take a channel that passes $\boldsymbol{H}$ unchanged and generates $\mathbb{Y}$ according to the following distribution

$$Q_{\mathbb{Y} \mid \boldsymbol{H}=\boldsymbol{h}, \boldsymbol{X}=\boldsymbol{x}} = \prod_{j=1}^{n} \mathcal{CN}(\mathbf{0}, \mathsf{I}_r + \rho \boldsymbol{h}\boldsymbol{h}^{\mathsf{H}}). \tag{45}$$

In particular, $\mathbb{Y}$ and $\boldsymbol{X}$ are conditionally independent given $\boldsymbol{H}$. Since $\boldsymbol{H}$ and the message J are independent, $\mathbb{Y}$ and J are independent under the auxiliary Q-channel. Hence, the average error probability ϵ' under the auxiliary Q-channel is bounded as

$$\epsilon' \ge 1 - \frac{1}{M}. \tag{46}$$

Then, [5, Thm. 26]

$$\begin{aligned} &nR^*_{\mathrm{e}}(n,\epsilon) \\ &\quad \le \sup_{P_{\boldsymbol{X} \mid \boldsymbol{H}}} \log\left(\frac{1}{\beta_{1-\epsilon}(P_{\boldsymbol{X}\mathbb{Y}\boldsymbol{H}}, P_{\boldsymbol{H}} P_{\boldsymbol{X} \mid \boldsymbol{H}} Q_{\mathbb{Y} \mid \boldsymbol{H}})}\right) \end{aligned} \tag{47}$$

where $\beta_{1-\epsilon}(\cdot,\cdot)$ is defined in (4), and the supremum is over all conditional distributions $P_{\boldsymbol{X} \mid \boldsymbol{H}}$ supported on $\mathcal{F}_n$. We next note that, by the spherical symmetry of $\mathcal{F}_n$ and of (45), the function $\beta_\alpha(P_{\mathbb{Y} \mid \boldsymbol{X}=\boldsymbol{x}, \boldsymbol{H}=\boldsymbol{h}}, Q_{\mathbb{Y} \mid \boldsymbol{H}=\boldsymbol{h}})$ does not depend on $\boldsymbol{x} \in \mathcal{F}_n$. By [5, Lem. 29], this implies

$$\begin{aligned} &\beta_\alpha(P_{\boldsymbol{X}\mathbb{Y} \mid \boldsymbol{H}=\boldsymbol{h}}, P_{\boldsymbol{X} \mid \boldsymbol{H}=\boldsymbol{h}} Q_{\mathbb{Y} \mid \boldsymbol{H}=\boldsymbol{h}}) \\ &\quad = \beta_\alpha(P_{\mathbb{Y} \mid \boldsymbol{X}=\boldsymbol{x}_0, \boldsymbol{H}=\boldsymbol{h}}, Q_{\mathbb{Y} \mid \boldsymbol{H}=\boldsymbol{h}}) \end{aligned} \tag{48}$$

(with $\boldsymbol{x}_0$ defined in (32)) for every $P_{\boldsymbol{X} \mid \boldsymbol{H}=\boldsymbol{h}}$ supported on $\mathcal{F}_n$, every $\boldsymbol{h} \in \mathbb{C}^r$, and every α. Consider the optimal test Z for

$P_{\boldsymbol{X}\mathbb{Y}\boldsymbol{H}}$ versus $P_{\boldsymbol{H}}P_{\boldsymbol{X}\,|\,\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}$ under the constraint that

$$P_{\boldsymbol{X}\mathbb{Y}\boldsymbol{H}}[Z=1] = \int \underbrace{P_{\boldsymbol{X}\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}[Z=1]}_{\triangleq \alpha(\boldsymbol{h})} dP_{\boldsymbol{H}}(\boldsymbol{h}) \geq 1-\epsilon. \tag{49}$$

We have that

$$\begin{aligned}
&\beta_{1-\epsilon}(P_{\boldsymbol{X}\mathbb{Y}\boldsymbol{H}}, P_{\boldsymbol{H}}P_{\boldsymbol{X}\,|\,\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}) \\
&\quad = \int P_{\boldsymbol{X}\,|\,\boldsymbol{H}=\boldsymbol{h}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}[Z=1] dP_{\boldsymbol{H}}(\boldsymbol{h}) && (50)\\
&\quad \geq \int \beta_{\alpha(\boldsymbol{h})}(P_{\boldsymbol{X}\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}, P_{\boldsymbol{X}\,|\,\boldsymbol{H}=\boldsymbol{h}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}) dP_{\boldsymbol{H}}(\boldsymbol{h}) && (51)\\
&\quad = \int \beta_{\alpha(\boldsymbol{h})}(P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}=\boldsymbol{h}}, Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}) dP_{\boldsymbol{H}}(\boldsymbol{h}) && (52)
\end{aligned}$$

where (52) follows from (48). Fix an arbitrary $\boldsymbol{h} \in \mathbb{C}^r$, and let $Z^*_{\boldsymbol{h}}$ be an optimal test between $P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}=\boldsymbol{h}}$ and $Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}$, i.e., a test satisfying

$$P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}=\boldsymbol{h}}[Z^*_{\boldsymbol{h}}=1] \geq \alpha(\boldsymbol{h}) \tag{53}$$

and

$$Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}[Z^*_{\boldsymbol{h}}=1] = \beta_{\alpha(\boldsymbol{h})}(P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}=\boldsymbol{h}}, Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}). \tag{54}$$

Then $Z^*_{\boldsymbol{H}}$ is a test between $P_{\boldsymbol{H}}P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}}$ and $P_{\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}$. Moreover,

$$\begin{aligned}
\int P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}=\boldsymbol{h}}[Z^*_{\boldsymbol{h}}=1] dP_{\boldsymbol{H}}(\boldsymbol{h}) &\geq \int \alpha(\boldsymbol{h}) dP_{\boldsymbol{H}}(\boldsymbol{h}) && (55)\\
&\geq 1-\epsilon && (56)
\end{aligned}$$

where (56) follows from (49). Consequently,

$$\begin{aligned}
&\int \beta_{\alpha(\boldsymbol{h})}(P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}=\boldsymbol{h}}, Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}) dP_{\boldsymbol{H}}(\boldsymbol{h}) \\
&\quad = \int Q_{\mathbb{Y}\,|\,\boldsymbol{H}=\boldsymbol{h}}[Z^*_{\boldsymbol{h}}=1] dP_{\boldsymbol{H}}(\boldsymbol{h}) && (57)\\
&\quad \geq \beta_{1-\epsilon}(P_{\boldsymbol{H}}P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}}, P_{\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}) && (58)
\end{aligned}$$

where (57) follows from (54), and (58) follows by the definition of $\beta_{1-\epsilon}(\cdot,\cdot)$ and by (56). Substituting (58) into (52), we obtain that

$$\begin{aligned}
&\beta_{1-\epsilon}(P_{\boldsymbol{X}\mathbb{Y}\boldsymbol{H}}, P_{\boldsymbol{H}}P_{\boldsymbol{X}\,|\,\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}) \\
&\quad \geq \beta_{1-\epsilon}(P_{\boldsymbol{H}}P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}}, P_{\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}) && (59)
\end{aligned}$$

for every $P_{\boldsymbol{X}\,|\,\boldsymbol{H}}$ supported on $\mathcal{F}_n$. It can be shown that (59) holds, in fact, with equality.

In the following, to shorten notation, we define

$$P_0 \triangleq P_{\boldsymbol{H}}P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}_0,\boldsymbol{H}}, \quad Q_0 \triangleq P_{\boldsymbol{H}}Q_{\mathbb{Y}\,|\,\boldsymbol{H}}. \tag{60}$$

Using this notation, (47) becomes

$$nR^*_{\mathrm{e}}(n,\epsilon) \leq -\log \beta_{1-\epsilon}(P_0, Q_0). \tag{61}$$

Let

$$r(\boldsymbol{x}_0; \mathbb{Y}\boldsymbol{H}) \triangleq \log \frac{dP_0}{dQ_0}. \tag{62}$$

By the Neyman-Pearson lemma (see for example [12, p. 23]),

$$\beta_{1-\epsilon}(P_0, Q_0) = Q_0\big[r(\boldsymbol{x}_0; \mathbb{Y}\boldsymbol{H}) \geq n\gamma_n\big] \tag{63}$$

where γ_n is the solution of

$$P_0\big[r(\boldsymbol{x}_0; \mathbb{Y}\boldsymbol{H}) \leq n\gamma_n\big] = \epsilon. \tag{64}$$

We conclude the proof by noting that, under Q_0, the random variable $r(\boldsymbol{x}_0; \mathbb{Y}\boldsymbol{H})$ has the same distribution as L_n in (17), and under P_0, it has the same distribution as S_n in (18).

Appendix B
Proof of Corollary 3

Due to spherical symmetry and to the assumption that $\boldsymbol{x} \in \mathcal{F}_n$, the term $P_{\mathbb{Y}\,|\,\boldsymbol{X}=\boldsymbol{x}}[\cos^2\theta(\boldsymbol{x},\mathbb{Y}) \geq 1-\gamma_n]$ on the LHS of (26), does not depend on $\boldsymbol{x}$. Hence, we can set $\boldsymbol{x} = \boldsymbol{x}_0$.

We next evaluate $\sup_{\boldsymbol{x}\in\mathcal{F}_n} Q_{\mathbb{Y}}[Z_{\boldsymbol{x}}(\mathbb{Y})=1]$ for the Gaussian distribution $Q_{\mathbb{Y}}$ in (28). Under $Q_{\mathbb{Y}}$, the random subspace spanned by the columns of $\mathbb{Y}$ is r-dimensional with probability one, and is uniformly distributed on the Grassmann manifold of r-planes in $\mathbb{C}^n$ [13, Sec. 6]. If we take $\boldsymbol{A} \sim Q_{\boldsymbol{A}} = \mathcal{CN}(\mathbf{0}, \mathsf{I}_n)$ to be independent of $\mathbb{Y} \sim Q_{\mathbb{Y}}$, then for every $\boldsymbol{x} \in \mathcal{F}_n$ and every $\mathsf{Y} \in \mathbb{C}^{n\times r}$ with full column rank

$$\begin{aligned}
Q_{\mathbb{Y}}[Z_{\boldsymbol{x}}(\mathbb{Y})=1] &= Q_{\mathbb{Y},\boldsymbol{A}}[Z_{\boldsymbol{A}}(\mathbb{Y})=1] && (65)\\
&= Q_{\boldsymbol{A}}[Z_{\boldsymbol{A}}(\mathsf{Y})=1]. && (66)
\end{aligned}$$

In (65) we used that $Q_{\mathbb{Y}}[Z_{\boldsymbol{x}}(\mathbb{Y})=1]$ does not depend on $\boldsymbol{x}$; (66) holds because $Q_{\boldsymbol{A}}$ is isotropic.

To compute the RHS of (66), we will choose for simplicity

$$\mathsf{Y} = \begin{bmatrix} \mathsf{I}_r \\ \mathbf{0}_{(n-r)\times r} \end{bmatrix}. \tag{67}$$

The columns of Y are orthonormal. Hence, by (24) and (26)

$$\begin{aligned}
Q_{\boldsymbol{A}}[Z_{\boldsymbol{A}}(\mathsf{Y})=1] &= Q_{\boldsymbol{A}}\left[\frac{\|\boldsymbol{A}^{\mathsf{H}}\mathsf{Y}\|^2}{\|\boldsymbol{A}\|^2} \geq 1-\gamma_n\right] && (68)\\
&= Q_{\boldsymbol{A}}\left[\frac{\sum_{i=r+1}^n |A_i|^2}{\sum_{i=1}^n |A_i|^2} \leq \gamma_n\right] && (69)
\end{aligned}$$

where $A_i \sim \mathcal{CN}(0,1)$ is the ith entry of $\boldsymbol{A}$. Observe that the ratio

$$\frac{\sum_{i=r+1}^n |A_i|^2}{\sum_{i=1}^n |A_i|^2} \tag{70}$$

is $\mathrm{Beta}(n-r, r)$-distributed [9, Ch. 25.2].

To conclude the proof, we need to compute $\tilde{\kappa}_\tau(\mathcal{F}_n, Q_{\mathbb{Y}})$. If we replace the constraint i) in (21) by the less stringent constraint that

$$P_{\mathbb{Y}}[Z(\mathbb{Y})=1] = \mathbb{E}_{P_{\boldsymbol{X}}^{(\text{unif})}}\big[P_{\mathbb{Y}\,|\,\boldsymbol{X}}[Z(\mathbb{Y})=1]\big] \geq \tau \tag{71}$$

with $P_{\mathbb{Y}}$ being the output distribution induced by the uniform input distribution $P_{\boldsymbol{X}}^{(\text{unif})}$ on $\mathcal{F}_n$, we get an infimum in (21), which we denote by $\bar{\kappa}_\tau$, that is no larger than $\tilde{\kappa}_\tau(\mathcal{F}_n, Q_{\mathbb{Y}})$. Because both $Q_{\mathbb{Y}}$ and the output distribution $P_{\mathbb{Y}}$ induced by $P_{\boldsymbol{X}}^{(\text{unif})}$ are isotropic, we conclude that

$$P_{\mathbb{Y}}[Z(\mathbb{Y})=1] = Q_{\mathbb{Y}}[Z(\mathbb{Y})=1] \geq \tau \tag{72}$$

for all tests $Z(\mathbb{Y})$ that satisfy (71) and the constraint ii) in (21). Therefore,

$$\tilde{\kappa}_\tau(\mathcal{F}_n, Q_{\mathbb{Y}}) \geq \bar{\kappa}_\tau = \tau. \tag{73}$$

Appendix C
Proof of Lemma 4

By assumption, there exist $\delta > 0$ and $k_2 < \infty$, such that

$$\max\{|f_Y(t)|, |f_Y'(t)|, |f_Y''(t)|\} \le k_2 \tag{74}$$

for all $t \in (-\delta, \delta)$. Let F_Y be the cdf of Y. We write

$$\begin{aligned}\mathbb{P}[X \le \sqrt{n}Y] &= \int_{|x|\ge\delta\sqrt{n}} \mathbb{P}[Y \ge x/\sqrt{n}]dP_X \\ &\quad + \int_{|x|<\delta\sqrt{n}} \mathbb{P}[Y \ge x/\sqrt{n}]dP_X \qquad (75)\\ &= \int_{|x|\ge\delta\sqrt{n}} \mathbb{P}[Y \ge x/\sqrt{n}]dP_X \\ &\quad + \int_{|x|<\delta\sqrt{n}} (1 - F_Y(x/\sqrt{n}))dP_X. \qquad (76)\end{aligned}$$

We next evaluate the two terms on the RHS of (76). For the first term, we have that

$$\begin{aligned}\int_{|x|\ge\delta\sqrt{n}} \mathbb{P}[Y \ge x/\sqrt{n}]dP_X &\le \int_{|x|\ge\delta\sqrt{n}} dP_X \qquad (77)\\ &\le \frac{\mathbb{E}\left[|X|^3\right]}{\delta^3 n^{3/2}} \qquad (78)\end{aligned}$$

where (78) follows from Markov's inequality. To compute the second term on the RHS of (76), we note that, by Taylor's theorem [14, Thm. 5.15], for all $x \in (-\delta\sqrt{n}, \delta\sqrt{n})$,

$$\begin{aligned}&F_Y(x/\sqrt{n}) \\ &\quad = F_Y(0) + f_Y(0)\frac{x}{\sqrt{n}} + \frac{f_Y'(0)}{2}\frac{x^2}{n} + \frac{f_Y''(x_0)}{6}\frac{x^3}{n^{3/2}} \qquad (79)\end{aligned}$$

for some $x_0 \in (0, x/\sqrt{n})$. Averaging over X, we get

$$\begin{aligned}&\int_{|x|<\delta\sqrt{n}} F_Y(x/\sqrt{n})dP_X \\ &\quad = F_Y(0)(1 - \underbrace{\mathbb{P}[|x| \ge \delta\sqrt{n}]}_{\le\delta^{-3}\mathbb{E}[|X|^3]n^{-3/2}}) \\ &\qquad + \frac{f_Y(0)}{\sqrt{n}} \underbrace{\mathbb{E}\left[X \cdot \mathbb{1}\{|X| < \delta\sqrt{n}\}\right]}_{\triangleq c_1(n)} \\ &\qquad + \frac{f_Y'(0)}{2n}\left(\mathbb{E}\left[X^2\right] - \underbrace{\mathbb{E}\left[X^2 \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right]}_{\triangleq c_2(n)}\right) \\ &\qquad + \underbrace{\mathbb{E}\left[\frac{X^3 f_Y''(X_0)}{6n^{3/2}} \cdot \mathbb{1}\{|X| < \delta\sqrt{n}\}\right]}_{\triangleq c_3(n)}. \qquad (80)\end{aligned}$$

The term $c_1(n)$ can be bounded as

$$\begin{aligned}|c_1(n)| &= \left|\underbrace{\mathbb{E}[X]}_{=0} - \mathbb{E}\left[X \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right]\right| \qquad (81)\\ &= \left|\mathbb{E}\left[X \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right]\right| \qquad (82)\\ &\le \mathbb{E}\left[|X| \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right] \qquad (83)\\ &= \frac{1}{\delta^2 n}\mathbb{E}\left[\delta^2 n|X| \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right] \qquad (84)\\ &\le \frac{1}{\delta^2 n}\mathbb{E}\left[|X|^3 \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right]. \qquad (85)\end{aligned}$$

The term $c_2(n)$ can be bounded as

$$\begin{aligned}|c_2(n)| &= \frac{1}{\delta\sqrt{n}}\mathbb{E}\left[\delta\sqrt{n} \cdot |X|^2 \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right] \qquad (86)\\ &\le \frac{1}{\delta\sqrt{n}}\mathbb{E}\left[|X|^3 \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right]. \qquad (87)\end{aligned}$$

Finally, $c_3(n)$ can be bounded as

$$\begin{aligned}|c_3(n)| &\le \mathbb{E}\left[\frac{|X|^3|f_Y''(X_0)|}{6n^{3/2}} \cdot \mathbb{1}\{|X| < \delta\sqrt{n}\}\right] \qquad (88)\\ &\le \underbrace{\mathbb{E}\left[|X|^3 \cdot \mathbb{1}\{|X| < \delta\sqrt{n}\}\right]}_{\le\mathbb{E}[|X|^3]}\frac{k_2}{6n^{3/2}}. \qquad (89)\end{aligned}$$

Here, (89) follows because $|f_Y''(x_0)| \le k_2$ by assumption. Combining (76) and (80), we obtain

$$\begin{aligned}&n^{3/2}\left|\mathbb{P}[X \le \sqrt{n}Y] - \mathbb{P}[Y \ge 0] + \frac{f_Y'(0)}{2n}\right| \\ &= n^{3/2}\left|\int_{|x|\ge\delta\sqrt{n}} \mathbb{P}[Y \ge x/\sqrt{n}]dP_X \right.\\ &\qquad + \underbrace{(1 - F_Y(0))}_{\le 1}\mathbb{P}[|X| \ge \delta\sqrt{n}] \\ &\qquad \left. - \frac{f_Y(0)}{\sqrt{n}}c_1(n) + \frac{f_Y'(0)}{2n}c_2(n) - c_3(n)\right| \qquad (90)\\ &\le \delta^{-3}\mathbb{E}\left[|X|^3\right] + \delta^{-3}\mathbb{E}\left[|X|^3\right] + \frac{k_2\mathbb{E}\left[|X|^3\right]}{6} \\ &\qquad + k_2\underbrace{\left(\delta^{-2} + (2\delta)^{-1}\right)\mathbb{E}\left[|X|^3 \cdot \mathbb{1}\{|X| \ge \delta\sqrt{n}\}\right]}_{\triangleq c_4(n)} \qquad (91)\\ &= (k_2/6 + 2\delta^{-3})\mathbb{E}\left[|X|^3\right] + k_2 c_4(n) \qquad (92)\end{aligned}$$

where (91) follows from (78), (85) and (87). The proof is concluded by taking $n \to \infty$ on each side of (92), and by using that

$$\lim_{n\to\infty} c_4(n) = 0. \tag{93}$$

Appendix D
Proof of Theorem 5

To establish Theorem 5, we study the converse bound (19) and the achievability bound (30) in the large-n limit.

A. Converse

We begin by upper-bounding the RHS of (19) by recalling that for every $\gamma > 0$ [5, Eq. (102)]

$$\alpha \le P\left[\frac{dP}{dQ} \ge \gamma\right] + \gamma\beta_\alpha(P, Q). \tag{94}$$

Using (94) on (63) and setting $\gamma = e^{n\gamma_n}$ we obtain

$$\begin{aligned}&\beta_{1-\epsilon}(P_0, Q_0) \\ &\quad \ge e^{-n\gamma_n}\left(1 - \epsilon - P_0[r(\boldsymbol{x}_0; \mathbb{Y}\boldsymbol{H}) \ge n\gamma_n]\right) \qquad (95)\\ &\quad = e^{-n\gamma_n}\left(P_0[r(\boldsymbol{x}_0; \mathbb{Y}\boldsymbol{H}) \le n\gamma_n] - \epsilon\right). \qquad (96)\end{aligned}$$

This allows us to upper-bound the RHS of (19) as

$$R^*_{\mathrm{rt}}(n-1,\epsilon) \le \frac{n}{n-1}\left[\gamma_n - \frac{1}{n}\log\big(\mathbb{P}[S_n \le n\gamma_n]-\epsilon\big)\right] \quad (97)$$

for every γ_n satisfying

$$\mathbb{P}[S_n \le n\gamma_n] \ge \epsilon. \quad (98)$$

We shall take γ_n so that

$$\mathbb{P}[S_n \le n\gamma_n] = \epsilon + \frac{1}{n}. \quad (99)$$

For this choice of γ_n, (97) reduces to

$$R^*_{\mathrm{rt}}(n-1,\epsilon) \le \frac{n}{n-1}\left[\gamma_n + \frac{\log n}{n}\right]. \quad (100)$$

The proof is completed by showing that (99) holds for

$$\gamma_n = C_\epsilon + \mathcal{O}(1/n). \quad (101)$$

To prove (101), we evaluate $\mathbb{P}[S_n \le n\gamma_n]$ in the limit $n\to\infty$ up to a $o(1/n)$ term. Note that, given G, the random variable S_n is the sum of n i.i.d. random variables with mean $\mu(G) \triangleq \log(1+\rho G)$ and variance

$$\sigma^2(G) \triangleq \frac{\rho G(\rho G+2)}{(1+\rho G)^2}. \quad (102)$$

Hence,

$$\mathbb{P}[S_n \le n\xi] = \mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^{n} T_j \le \sqrt{n}U(\xi)\right] \quad (103)$$

where

$$T_j \triangleq \frac{1}{\sigma(G)}\left(1 - \frac{\left|\sqrt{\rho G}Z_i - 1\right|^2}{1+\rho G}\right) \quad (104)$$

are zero-mean, unit-variance random variables that are conditionally independent given G, and[5]

$$U(\xi) \triangleq \frac{\xi - \mu(G)}{\sigma(G)}. \quad (105)$$

The following lemma, which is based on a Cramer-Esseen-type central-limit theorem [8, Thm. VI.1] and on Lemma 4, shows that (103) can be closely approximated by $\mathbb{P}[U(\xi)\ge 0]$.

Lemma 6: Let $\{T_j\}_{j=1}^n$ be given in (104) and let $U(\xi)$ be given in (105) with G satisfying the assumptions in Theorem 5. Take an arbitrary $\xi_0 > 0$ that satisfies $\mathbb{P}[U(\xi_0)\ge 0] > 0$. Then there exists a $\delta > 0$ so that

$$\lim_{n\to\infty} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} n^{3/2}\left|\mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^{n} T_j \le \sqrt{n}U(\xi)\right] - \mathbb{P}[U(\xi)\ge 0] + \frac{q(\xi)}{2n}\right| < \infty \quad (106)$$

where

$$q(\xi) \triangleq f'_{U(\xi)}(0) \quad (107)$$

$$= -\frac{e^{2\xi}-1}{\rho^2}f'_G\left(\frac{e^\xi-1}{\rho}\right) - \frac{e^{-\xi}+e^{\xi}}{\rho}f_G\left(\frac{e^\xi-1}{\rho}\right). \quad (108)$$

Proof: See Appendix E. ■

Note that

$$\mathbb{P}[U(\xi)\ge 0] = \mathbb{P}[\mu(G)\le\xi] = F_C(\xi) \quad (109)$$

where $F_C(\xi)$ is defined in (15). Hence, setting $\xi = \gamma_n$ and $\xi_0 = C_\epsilon$, we get

$$\mathbb{P}[S_n \le n\gamma_n] = F_C(\gamma_n) - \frac{q(\gamma_n)}{2n} + \mathcal{O}(n^{-3/2}) \quad (110)$$

where $\mathcal{O}(n^{-3/2})$ is uniform in $\gamma_n \in (C_\epsilon-\delta, C_\epsilon+\delta)$ for some $\delta>0$. Substituting (110) into (99), we finally obtain

$$F_C(\gamma_n) - \frac{q(\gamma_n)}{2n} + \mathcal{O}(n^{-3/2}) = \epsilon + \frac{1}{n}. \quad (111)$$

By Taylor's theorem [14, Thm. 5.15]

$$F_C(\gamma_n) = F_C(C_\epsilon) + \left(\left.\frac{dF_C(\xi)}{d\xi}\right|_{\xi=C_\epsilon} + o(1)\right)(\gamma_n - C_\epsilon). \quad (112)$$

Substituting (112) into (111) and using that $F_C(C_\epsilon)=\epsilon$, we get

$$\gamma_n = C_\epsilon + \frac{q(C_\epsilon)+2}{2n}\cdot\frac{1}{\left.\frac{dF_C(\xi)}{d\xi}\right|_{\xi=C_\epsilon}} + o(1/n). \quad (113)$$

The proof of (101) is concluded by noting that, by assumption, $q(C_\epsilon) < \infty$ and $\left.\frac{dF_C(\xi)}{d\xi}\right|_{\xi=C_\epsilon} > 0$.

B. Achievability

We set $\tau = 1/n$ and $\gamma_n = \exp(-C_\epsilon + \mathcal{O}(1/n))$ in (30) and we use that

$$F(\gamma_n; n-r, r) \le \frac{\Gamma(n)}{\Gamma(n-r)\Gamma(r)}\int_0^{\gamma_n} t^{(n-r)-1}dt \quad (114)$$

$$= \frac{\Gamma(n)}{\Gamma(n-r+1)\Gamma(r)}\gamma_n^{n-r} \quad (115)$$

$$\le n^{r-1}\gamma_n^{n-r}. \quad (116)$$

This yields,

$$\frac{\log M}{n} \ge C_\epsilon - r\frac{\log(n)}{n} + \mathcal{O}\left(\frac{1}{n}\right). \quad (117)$$

To conclude the proof, we show that the choice $\gamma_n = \exp(-C_\epsilon + \mathcal{O}(1/n))$ satisfies

$$P_{\mathbb{Y}|\boldsymbol{X}=\boldsymbol{x}_0}[Z_{\boldsymbol{x}_0}(\mathbb{Y})=1] \ge 1-\epsilon+1/n. \quad (118)$$

Given $\boldsymbol{H}=\boldsymbol{h}\neq\boldsymbol{0}$, we have that[6]

$$\cos\theta(\boldsymbol{x}_0,\mathbb{Y}) = \max_{\boldsymbol{a}\in\mathbb{C}^r\setminus\{\boldsymbol{0}\}}\frac{|<\boldsymbol{x}_0,\mathbb{Y}\boldsymbol{a}>|}{\|\boldsymbol{x}_0\|\|\mathbb{Y}\boldsymbol{a}\|} \quad (119)$$

$$\ge \frac{|<\boldsymbol{x}_0,\mathbb{Y}\overline{\boldsymbol{h}}>|}{\|\boldsymbol{x}_0\|\|\mathbb{Y}\overline{\boldsymbol{h}}\|}. \quad (120)$$

[5]We shall write $U(\xi)$ simply as U whenever stressing its dependence on ξ is unnecessary.

[6]Note that $\boldsymbol{H}=\boldsymbol{0}$ with zero probability.

Then

$$
\begin{aligned}
&P_{\mathbb{Y} \mid \boldsymbol{X}=\boldsymbol{x}_0}[\cos^2\theta(\boldsymbol{x}_0,\mathbb{Y}) \geq 1-\gamma_n] \\
&\quad = \mathbb{E}_{\boldsymbol{H}}\left[P_{\mathbb{Y} \mid \boldsymbol{H}=\boldsymbol{h},\boldsymbol{X}=\boldsymbol{x}_0}[\cos^2\theta(\boldsymbol{x}_0,\mathbb{Y}) \geq 1-\gamma_n]\right] && (121)\\
&\quad \geq \mathbb{E}_{\boldsymbol{H}}\left[P_{\mathbb{Y} \mid \boldsymbol{H}=\boldsymbol{h},\boldsymbol{X}=\boldsymbol{x}_0}\left[\frac{|<\boldsymbol{x}_0,\mathbb{Y}\overline{\boldsymbol{h}}>|^2}{\|\boldsymbol{x}_0\|^2\|\mathbb{Y}\overline{\boldsymbol{h}}\|^2} \geq 1-\gamma_n\right]\right] && (122)\\
&\quad = P_{\mathbb{Y}\boldsymbol{H} \mid \boldsymbol{X}=\boldsymbol{x}_0}\left[\frac{|<\boldsymbol{x}_0,\mathbb{Y}\overline{\boldsymbol{H}}>|^2}{\|\boldsymbol{x}_0\|^2\|\mathbb{Y}\overline{\boldsymbol{H}}\|^2} \geq 1-\gamma_n\right]. && (123)
\end{aligned}
$$

Under $P_{\mathbb{Y}\boldsymbol{H} \mid \boldsymbol{X}=\boldsymbol{x}_0}$, the term $|<\boldsymbol{x}_0,\mathbb{Y}\overline{\boldsymbol{H}}>|^2/(\|\boldsymbol{x}_0\|^2\|\mathbb{Y}\overline{\boldsymbol{H}}\|^2)$ is distributed as

$$
\frac{\left|\sqrt{n\rho}\|\boldsymbol{H}\|^2 + n^{-1/2}\sum_{j=1}^n \boldsymbol{W}_j^{\mathsf{H}}\boldsymbol{H}\right|^2}{\sum_{i=1}^n \left|\sqrt{\rho}\|\boldsymbol{H}\|^2 + \boldsymbol{W}_j^{\mathsf{H}}\boldsymbol{H}\right|^2} \tag{124}
$$

where $\boldsymbol{W}_j \sim \mathcal{CN}(\boldsymbol{0},\mathsf{I}_r)$. Note that $\boldsymbol{W}_j^{\mathsf{H}}\boldsymbol{H}$ has the same distribution as $\sqrt{G}Z_j$, where $Z_j \sim \mathcal{CN}(0,1)$. Hence, the random ratio in (124) is distributed as

$$
\frac{\left|\sqrt{nG\rho} + n^{-1/2}\sum_{i=1}^n Z_i\right|^2}{\sum_{i=1}^n \left|Z_i + \sqrt{G\rho}\right|^2}. \tag{125}
$$

Therefore,

$$
\begin{aligned}
&P_{\mathbb{Y}\boldsymbol{H} \mid \boldsymbol{X}=\boldsymbol{x}_0}\left[\frac{|<\boldsymbol{x}_0,\mathbb{Y}\overline{\boldsymbol{H}}>|^2}{\|\boldsymbol{x}\|^2\|\mathbb{Y}\overline{\boldsymbol{H}}\|^2} \geq 1-\gamma_n\right] \\
&\quad = \mathbb{P}\left[\frac{\left|\sqrt{nG\rho} + n^{-1/2}\sum_{i=1}^n Z_i\right|^2}{\sum_{i=1}^n \left|Z_i + \sqrt{G\rho}\right|^2} \geq 1-\gamma_n\right] && (126)\\
&\quad = \mathbb{P}\left[\frac{\sum_{i=1}^n |Z_i|^2 - \left|\sum_{i=1}^n Z_i\right|^2/n}{\sum_{i=1}^n \left|Z_i + \sqrt{G\rho}\right|^2} \leq \gamma_n\right] && (127)\\
&\quad \geq \mathbb{P}\left[\frac{\sum_{i=1}^n |Z_i|^2}{\sum_{i=1}^n \left|Z_i + \sqrt{G\rho}\right|^2} \leq \gamma_n\right] && (128)\\
&\quad = \mathbb{P}\left[\sum_{i=1}^n \left|(1-\gamma_n)Z_i - \gamma_n\sqrt{G\rho}\right|^2 \leq n\gamma_n G\rho\right] && (129)\\
&\quad = \mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^n \widetilde{T}_j \leq \sqrt{n}\widetilde{U}\right] && (130)
\end{aligned}
$$

where

$$
\widetilde{U} \triangleq \frac{\gamma_n G\rho - \tilde{\mu}(G)}{\sigma(G)} = \frac{\gamma_n(1+G\rho)-1}{\sqrt{(1-\gamma_n)^2 + 2\gamma_n^2 G\rho}} \tag{131}
$$

and

$$
\widetilde{T}_j \triangleq \frac{1}{\tilde{\sigma}(G)}\left(\left|(1-\gamma_n)Z_i - \gamma_n\sqrt{G\rho}\right|^2 - \tilde{\mu}(G)\right) \tag{132}
$$

with

$$
\tilde{\mu}(G) \triangleq (1-\gamma_n)^2 + \gamma_n^2 G\rho \tag{133}
$$

and

$$
\tilde{\sigma}^2(G) \triangleq (1-\gamma_n)^2\left[(1-\gamma_n)^2 + 2\gamma_n^2 G\rho\right]. \tag{134}
$$

Note that, $\{\widetilde{T}_j\}_{j=1}^n$ are zero-mean, unit-variance random variables that are conditionally independent given G.

To summarize, we showed that

$$
\begin{aligned}
&P_{\mathbb{Y} \mid \boldsymbol{X}=\boldsymbol{x}_0}[\cos^2\theta(\boldsymbol{x}_0,\mathbb{Y}) \geq 1-\gamma_n] \\
&\quad \geq \mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^n \widetilde{T}_j \leq \sqrt{n}\widetilde{U}\right]. && (135)
\end{aligned}
$$

To conclude the proof, it suffices to show that $\gamma_n = \exp(-C_\epsilon + \mathcal{O}(1/n))$ yields

$$
\mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^n \widetilde{T}_j \leq \sqrt{n}\widetilde{U}\right] = 1-\epsilon+\frac{1}{n}. \tag{136}
$$

To this end, we proceed along the lines of the converse proof to obtain

$$
\mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^n \widetilde{T}_j \leq \sqrt{n}\widetilde{U}\right] = \mathbb{P}[\widetilde{U} \geq 0] - \frac{\tilde{q}(\tilde{\gamma}_n)}{2n} + \mathcal{O}(n^{-3/2}) \tag{137}
$$

where

$$
\tilde{q}(\tilde{\gamma}_n) \triangleq f'_{\widetilde{U}}(0) = \frac{(e^{\tilde{\gamma}_n}-1)^2}{\rho^2}f'_G(\tilde{g}_0) + \frac{2}{\rho}f_G(\tilde{g}_0) \tag{138}
$$

with $\tilde{\gamma}_n \triangleq -\log\gamma_n$ and $\tilde{g}_0 \triangleq (e^{\tilde{\gamma}_n}-1)/\rho$, and where $\mathcal{O}(n^{-3/2})$ is uniform in $\tilde{\gamma}_n \in (C_\epsilon-\delta, C_\epsilon+\delta)$ for some $\delta>0$. We further have that

$$
\mathbb{P}[\widetilde{U} \geq 0] = \mathbb{P}[\log(1+G\rho) \geq \tilde{\gamma}_n] = 1 - F_C(\tilde{\gamma}_n). \tag{139}
$$

Substituting (138) and (139) into (137), and then (137) into (136), we get

$$
F_C(\tilde{\gamma}_n) + \frac{\tilde{q}(\tilde{\gamma}_n)}{2n} + \mathcal{O}(n^{-3/2}) = \epsilon - \frac{1}{n}. \tag{140}
$$

Finally, using the same steps as in (111)–(113), we obtain

$$
\begin{aligned}
\tilde{\gamma}_n &= C_\epsilon - \frac{\tilde{q}(C_\epsilon)+2}{2n}\frac{1}{\left.\frac{dF_C(\xi)}{d\xi}\right|_{\xi=C_\epsilon}} + o(1/n) && (141)\\
&= C_\epsilon + \mathcal{O}(1/n) && (142)
\end{aligned}
$$

where (142) follows because $\tilde{q}(C_\epsilon) < \infty$ and because $\left.\frac{dF_C(\xi)}{d\xi}\right|_{\xi=C_\epsilon} > 0$ by assumption. This concludes the proof.

Appendix E
Proof of Lemma 6

Fix $\xi_0 > 0$ satisfying $\mathbb{P}[U(\xi_0) \geq 0] > 0$. Observe that

$$
\mathbb{P}[U(\xi) \geq 0] = \mathbb{P}[\log(1+\rho G) \leq \xi] = F_C(\xi) \tag{143}
$$

where $F_C(\xi)$ is defined in (15). Since $F_C(\xi)$ is continuous in ξ, there exists $0<\delta<\xi_0$ so that $F_C(\xi)>0$ (and hence, $\mathbb{P}[U(\xi) \geq 0] > 0$) for every $\xi \in (\xi_0-\delta, \xi_0+\delta)$.

To establish Lemma 6, we will need the following version of the Cramer-Esseen Theorem.[7]

[7] The Berry-Esseen Theorem used in [5] to establish (1) yields asymptotic expansions up to a $\mathcal{O}(1/\sqrt{n})$ term. This is not sufficient here, since we need to establish an asymptotic expansion up to a $o(1/n)$ term.

Theorem 7: Let $\{X_i\}_{i=1}^n$ be a sequence of i.i.d. real random variables having zero mean and unit variance. Furthermore, let

$$v(t) \triangleq \mathbb{E}\left[e^{itX_1}\right], \text{ and } F_n(x) \triangleq \mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^{n} X_j \leq x\right]. \quad (144)$$

If $\mathbb{E}\left[|X_1|^4\right] < \infty$ and if $\sup_{|t|\geq\zeta} |v(t)| \leq k_0$ for some $k_0 < 1$, where $\zeta \triangleq 1/(12\mathbb{E}\left[|X_1|^3\right])$, then for all x and n

$$\left|F_n(x) - Q(-x) - k_1(1-x^2)e^{-x^2/2}\frac{1}{\sqrt{n}}\right| \\ \leq k_2\left\{n^{-1}(1+|x|)^{-4}\mathbb{E}\left[|X_1|^4\right] + n^6\left(k_0+\frac{1}{2n}\right)^n\right\}. \quad (145)$$

Here, $k_1 \triangleq \mathbb{E}\left[X_1^3\right]/(6\sqrt{2\pi})$, and k_2 is a positive constant independent of $\{X_i\}_{i=1}^n$ and x.

Proof: The inequality (145) is a consequence of the tighter inequality reported in [8, Thm. VI.1]. ■

To prove Lemma 6, we proceed as follows. Note that

$$\mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^{n} T_j \leq \sqrt{n}U\right] = \mathbb{E}_G\left[\mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^{n} T_j \leq \sqrt{n}U \middle| G\right]\right]. \quad (146)$$

We next estimate the conditional probability on the RHS of (146) using Theorem 7. In order to do so, we need to verify that there exists a $k_0 < 1$ such that $\sup_{g\in\mathbb{R}^+}\sup_{|t|>\zeta} |v_{T_j}(t)| \leq k_0$, where $v_{T_j}(t) = \mathbb{E}\left[e^{itT_j} \mid G=g\right]$. We start by evaluating ζ. For all $g \in \mathbb{R}^+$, it can be shown that

$$\mathbb{E}\left[|T_j|^4 \mid G=g\right] = \frac{15(\rho g)^2+36\rho g+12}{(\rho g+2)^2} \leq 15. \quad (147)$$

By Lyapunov's inequality [8, p. 18], this implies that

$$\mathbb{E}\left[|T_j|^3 \mid G=g\right] \leq \left(\mathbb{E}\left[|T_j|^4 \mid G=g\right]\right)^{3/4} \leq 15^{3/4}. \quad (148)$$

Hence,

$$\zeta = \frac{1}{12\mathbb{E}[|T_j|^3 \mid G=g]} \geq \frac{15^{-3/4}}{12} \triangleq \zeta_0. \quad (149)$$

By (149), we have that

$$\sup_{|t|>\zeta} |v_{T_j}(t)| \leq \sup_{|t|>\zeta_0} |v_{T_j}(t)| \quad (150)$$

where ζ_0 does not depend on g. We now compute $|v_{T_j}(t)|$. Observe that given $G = g$

$$T_j = \frac{1}{\sigma(g)} - \frac{\rho g}{2\sigma(g)(1+\rho g)}\underbrace{\left|\sqrt{2}Z_j - \sqrt{\frac{2}{\rho g}}\right|^2}_{\triangleq N_j} \quad (151)$$

where the term N_j follows a noncentral χ^2 distribution with two degrees of freedom and noncentrality parameter $2/(\rho g)$. If we let $v_{N_j} \triangleq \mathbb{E}\left[e^{itN_j}\right]$, then

$$\begin{aligned} |v_{T_j}(t)| &= \left|\exp\left(\frac{it}{\sigma(g)}\right)\right| \cdot \left|\mathbb{E}\left[\exp\left(\frac{-it\rho g N_j}{2\sigma(g)(1+\rho g)}\right)\right]\right| && (152)\\ &= \left|v_{N_j}\left(\frac{-\rho g t}{2\sigma(g)(1+\rho g)}\right)\right| && (153)\\ &= \exp\left(-\frac{t^2}{\rho g t^2+\rho g+2}\right)\left(1+\frac{\rho g t^2}{\rho g+2}\right)^{-1/2} && (154)\end{aligned}$$

where (154) follows from [15, p. 24]. Now, observe that the RHS of (154) is monotonically decreasing in t and monotonically increasing in g. Hence,

$$\begin{aligned} &\sup_{g\in\mathbb{R}^+}\sup_{|t|\geq\zeta_0} |v_{T_j}(t)| \\ &= \sup_{g\in\mathbb{R}^+}\sup_{|t|\geq\zeta_0}\left\{\exp\left(-\frac{t^2}{\rho g t^2+\rho g+2}\right)\left(1+\frac{\rho g t^2}{\rho g+2}\right)^{-1/2}\right\} && (155)\\ &= \sup_{g\in\mathbb{R}^+}\left\{\exp\left(-\frac{\zeta_0^2}{\rho g\zeta_0^2+\rho g+2}\right)\left(1+\frac{\rho g\zeta_0^2}{\rho g+2}\right)^{-1/2}\right\} && (156)\\ &\leq \frac{1}{\sqrt{1+\zeta_0^2}} < 1. && (157)\end{aligned}$$

Set $k_0 = 1/\sqrt{1+\zeta_0^2}$. As we verified that the conditions in Theorem 7 are met, we conclude that for all n

$$\begin{aligned} &\left|\mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^{n} T_j \leq \sqrt{n}U\right] - \mathbb{E}\left[Q(-\sqrt{n}U)\right]\right| \\ &\quad\leq \frac{k_3}{\sqrt{n}}\left|\mathbb{E}\left[(1-nU^2)e^{-nU^2/2}\right]\right| \\ &\quad\quad+ \frac{k_4}{n}\mathbb{E}\left[(1+|\sqrt{n}U|)^{-4}\right] + k_2 n^6\left(k_0+\frac{1}{2n}\right)^n && (158)\end{aligned}$$

where $k_3 \triangleq 15^{3/4}/(6\sqrt{2\pi})$ and $k_4 \triangleq 15k_2$. In view of (106), we note that the last term on the RHS of (158) satisfies

$$\lim_{n\to\infty} n^{3/2}\left(k_2 n^6\left(k_0+\frac{1}{2n}\right)^n\right) = 0. \quad (159)$$

Next, we prove the following two estimates

$$\lim_{n\to\infty}\sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} \sqrt{n}\mathbb{E}\left[\left(1+|\sqrt{n}U(\xi)|\right)^{-4}\right] \leq k_5 \quad (160)$$

$$\lim_{n\to\infty}\sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} n\left|\mathbb{E}\left[\left(1-n(U(\xi))^2\right)e^{-\frac{n(U(\xi))^2}{2}}\right]\right| \leq k_6 \quad (161)$$

for some constants $k_5, k_6 < \infty$. Note that since the map

$$(g,\xi) \mapsto \left(\frac{\xi-\mu(g)}{\sigma(g)}, \xi\right) \quad (162)$$

is a diffeomorphism (of class C^3) [16, p. 147] in the region $\xi > 0, g > 0$, the pdf $f_{U(\xi)}(t)$ of $U(\xi)$ and its first and second derivative are jointly continuous functions of (ξ, t), and, hence,

bounded on bounded sets. Specifically, for every $\xi \in (\xi_0 - \delta, \xi_0 + \delta)$ and every $\tilde{\delta} > 0$ there exists a $\tilde{k} < \infty$ so that

$$\sup_{t\in[-\tilde{\delta},\tilde{\delta}]} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} |f_{U(\xi)}(t)| \le \tilde{k} \quad (163)$$

$$\sup_{t\in[-\tilde{\delta},\tilde{\delta}]} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} |f'_{U(\xi)}(t)| \le \tilde{k} \quad (164)$$

$$\sup_{t\in[-\tilde{\delta},\tilde{\delta}]} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} |f''_{U(\xi)}(t)| \le \tilde{k}. \quad (165)$$

Fix now $\tilde{\delta} > 0$ and let $\tilde{k}$ as in (163)–(165). To prove (160), we proceed as follows:

$$\begin{aligned}
&\mathbb{E}\left[\left(1+|\sqrt{n}U|\right)^{-4}\right] \\
&= \mathbb{E}\left[(1+|\sqrt{n}U|)^{-4}\mathbb{1}\{|U|<\tilde{\delta}\}\right] \\
&\quad + \mathbb{E}\left[\left(1+|\sqrt{n}U|\right)^{-4}\mathbb{1}\{|U|\ge\tilde{\delta}\}\right] && (166)\\
&\le 2\tilde{k}\int_0^{\tilde{\delta}}(1+\sqrt{n}t)^{-4}dt + (1+\sqrt{n}\tilde{\delta})^{-4} && (167)\\
&= \frac{2\tilde{k}}{3\sqrt{n}}\left(1-(1+\sqrt{n}\tilde{\delta})^{-3}\right) + (1+\sqrt{n}\tilde{\delta})^{-4} && (168)\\
&\le \frac{2\tilde{k}}{3\sqrt{n}} + \frac{1}{n^2\tilde{\delta}^4} && (169)
\end{aligned}$$

where in (167) we used (163). This proves (160). The inequality (161) can be established as follows. First, for $n \ge \tilde{\delta}^{-2}$,

$$\begin{aligned}
&\left|\mathbb{E}\left[(1-nU^2)e^{-nU^2/2}\right]\right| \\
&\le \underbrace{\left|\int_{-\tilde{\delta}}^{\tilde{\delta}}(1-nt^2)e^{-nt^2/2}f_U(t)dt\right|}_{\triangleq I_1} \\
&\quad + \underbrace{\mathbb{E}\left[(nU^2-1)e^{-nU^2/2}\mathbb{1}\{|U|\ge\tilde{\delta}\}\right]}_{\triangleq I_2}. && (170)
\end{aligned}$$

To evaluate I_1, we use the relation $(1-nt^2)e^{-nt^2/2} = \frac{d}{dt}\left(te^{-nt^2/2}\right)$ and integration by parts to obtain

$$\begin{aligned}
I_1 &= \left|\left(te^{-nt^2/2}f_U(t)\right)\Big|_{-\tilde{\delta}}^{\tilde{\delta}} - \int_{-\tilde{\delta}}^{\tilde{\delta}} te^{-nt^2/2}f'_U(t)dt\right| && (171)\\
&\le 2\tilde{k}\tilde{\delta}e^{-n\tilde{\delta}^2/2} + 2\tilde{k}\frac{1}{n}\left(1-e^{-n\tilde{\delta}^2/2}\right). && (172)
\end{aligned}$$

Therefore,

$$\lim_{n\to\infty} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} nI_1 \le 2\tilde{k}. \quad (173)$$

For I_2 we proceed as follows:

$$\begin{aligned}
I_2 &\le \mathbb{E}\left[nU^2e^{-nU^2/2}\cdot\mathbb{1}\{|U|\ge\tilde{\delta}\}\right] && (174)\\
&\le \sup_{|t|\ge\tilde{\delta}}\left\{nt^2e^{-nt^2/2}\right\}. && (175)
\end{aligned}$$

Note that when $n > 2\tilde{\delta}^{-2}$, the function $nt^2e^{-nt^2/2}$ is monotonically decreasing in $t \in [\tilde{\delta}, +\infty)$. Hence,

$$\lim_{n\to\infty} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} nI_2 \le \lim_{n\to\infty} n^2\tilde{\delta}^2e^{-n\tilde{\delta}^2/2} = 0. \quad (176)$$

Substituting (173) and (176) into (170), we obtain (161).

Combining (160) and (161) with (158), we conclude that

$$\begin{aligned}
\lim_{n\to\infty} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} n^{3/2}\Bigg|&\mathbb{P}\left[\frac{1}{\sqrt{n}}\sum_{j=1}^n T_j \le \sqrt{n}U(\xi)\right] \\
&-\mathbb{E}\left[Q(-\sqrt{n}U(\xi))\right]\Bigg| \le k_5 + k_6. \quad (177)
\end{aligned}$$

To conclude the proof of Lemma 6, we need to show that there exists a constant $k_7 < \infty$ such that

$$\begin{aligned}
\lim_{n\to\infty} \sup_{\xi\in(\xi_0-\delta,\xi_0+\delta)} n^{3/2}\Bigg|&\mathbb{E}\left[Q(-\sqrt{n}U(\xi))\right] \\
&-\mathbb{P}[U(\xi)\ge 0] + \frac{f'_{U(\xi)}(0)}{2n}\Bigg| \le k_7 \quad (178)
\end{aligned}$$

where $f_{U(\xi)}$ is the pdf of $U(\xi)$. This follows by the uniform bounds (163)–(165), and by (92). Note, in fact that the term $c_4(n)$ in the proof of Lemma 4, when evaluated for $Y = U(\xi)$, does not depend on ξ.

Since $U(\xi) = (\xi - \mu(G))/\sigma(G)$, we get after algebraic manipulations

$$\begin{aligned}
q(\xi) &= f'_{U(\xi)}(0) && (179)\\
&= -\frac{e^{2\xi}-1}{\rho^2}f'_G\left(\frac{e^{\xi}-1}{\rho}\right) - \frac{e^{-\xi}+e^{\xi}}{\rho}f_G\left(\frac{e^{\xi}-1}{\rho}\right). && (180)
\end{aligned}$$

This concludes the proof.

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